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PERINATAL EXPOSURE TO PHENOLS AND POLY- AND PERFLUOROALKYL SUBSTANCES AND GUT MICROBIOTA IN ONE-YEAR CHILDREN

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21 Abstract

The role of the gut microbiota on human health calls for a better understanding of 22 its determinants. In particular, the possible effects of chemicals with widespread exposure 23 24 other than pharmaceuticals are little known. Our aim was to characterize the sensitivity of the early-life gut microbiota to specific chemicals with possible antimicrobial action. 25 Within SEPAGES French couple-child cohort, we assessed 12 phenols in repeated urine 26 samples from 356 pregnant women and their offspring and 19 poly- and perfluoroalkyl 27 substances (PFAS) in serum from the pregnant women. We collected stool samples in the 28 children at one year of age, in which the V3-V4 region of 16S rRNA gene was sequenced, 29 30 allowing gut bacterial profiling. Associations of each chemical with α - and β -diversity indices of the gut microbiota, and with relative abundance of the most abundant taxa were 31 32 assessed using single-pollutant and mixture (BKMR) models. Perinatal exposure to certain parabens was associated with gut microbiota α - and β -diversity and with phyla Firmicutes 33 and Proteobacteria. Suggestive associations of certain phenols with genera of 34 Lachnospiraceae and Enterobacteriaceae families were observed, but not maintained after 35 correction for multiple testing. Parabens, which have known antimicrobial properties, 36 might disrupt the child gut microbiota, but larger studies are required. 37

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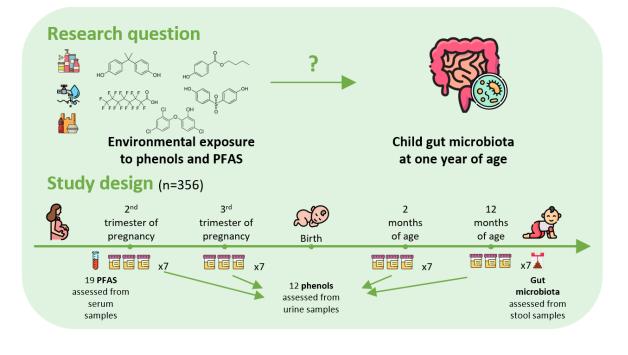
Key words: couple-child cohort / early-life gut microbiota / environmental exposures /
one-year children / perfluoroalkyl substances / phenols.

41 Synopsis

Growing evidence links the gut microbiota to human health and emphasizes the importance of understanding its determinants. Specific parabens, which are widespread pollutants with a predominantly dietary exposure pathway might influence the gut microbiota diversity in one-year children.

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47 **Table of Contents graphic**



48 49

50 Introduction

The microbiota represents all the microorganisms living in a specific environment. In humans, the gut microbiota develops during early childhood before stabilizing around the age of 3 years^{1,2}, it plays a role in digestive, metabolic, trophic, immune and neurological functions throughout life³⁻⁶. Dysbiosis of the gut microbiota has been correlated with many inflammatory and autoimmune conditions^{7,8} and the gut microbiota is also implicated in numerous neuropsychiatric⁹⁻¹³ and neurodevelopmental disorders such as autism spectrum disorders¹⁴⁻¹⁶.

It is therefore important to identify controllable causes of gut microbiota dysbiosis. 58 Known determinants of gut microbiota include the mode of delivery¹⁷, breastfeeding^{1,18}, 59 diet¹⁹, medical events, age, geographic location and sanitary conditions²⁰. Impact of 60 pharmaceutical drugs on the gut microbiota have been described $^{21-24}$, but research on the 61 62 sensitivity of the gut microbiota to other xenobiotics such as environmental chemicals has little been considered²⁵. A priori worth considering families of substances include those 63 64 with known antimicrobial properties, such as synthetic phenols. These comprise, among others, parabens and triclosan. 65

Parabens have been used for decades as preservatives in cosmetic and 66 pharmaceutical products, but also as food additives or in cleaning products, due to their 67 antibacterial and antifungal properties²⁶. Skin contacts with cosmetics or body care 68 products containing parabens represents one of the potential exposure routes for the 69 general population; exposure can also occur via the oral route, when consuming food or 70 pharmaceuticals containing parabens or ingesting house dust^{27–29}. Triclosan has been used 71 in some cosmetics, personal care products, textiles, and drugs for its antimicrobial 72 73 properties. Triclosan may be absorbed and reach systemic circulation through the mucous membrane of the oral cavity³⁰, by dermal exposure through the skin^{31,32}, and, after oral 74

exposure, through the gastrointestinal tract^{30,33,34}. A few toxicological studies have 75 investigated the impacts of triclosan exposure on the gut microbiota, mostly in fish or 76 rodent models, showing effects on the microbial diversity and composition^{35–39}. Low-dose 77 postnatal exposure to methylparaben, triclosan or their mixture also induced significant 78 changes in the overall bacterial gut microbiota composition in adolescent rats⁴⁰. In humans, 79 Ribado et al. found perturbation of maternal but not infant gut microbiota in 17 mother-80 baby pairs randomly assigned to use triclosan containing products, compared to 22 mother-81 baby pairs not assigned to triclosan products ⁴¹. Bever et *al*. found that the fecal microbiota 82 diversity of 31 exclusively breastfed infants exposed to breast milk with detectable 83 triclosan levels differed compared to their peers exposed to breast milk containing non-84 detectable amounts⁴². 85

Bisphenols are synthetic chemicals used in the production of polycarbonates, which 86 87 are transparent, rigid plastics used to make food containers in some countries, and in the production of epoxy resins found in protective coatings and linings for food and beverage 88 89 cans and vats. The dietary route through migration of bisphenols from packaging and containers into food and beverages consumed is the major source of bisphenol A exposure 90 for the general population. In animal models, effects of exposure to bisphenols A and S on 91 the gut microbiota have been suggested, with alterations described both in terms of 92 93 bacterial diversity and composition, and leading in some cases to functional profile changes in the microbial community $^{43-50}$. 94

Another chemical family of concern regarding health and the gut microbiota in particular are poly- and perfluoroalkyl substances (PFAS), a large family of fluorinated aliphatic compounds widely used as surfactant, water and grease repellents and found in all environmental compartments and in the food chain due to their high persistence^{26,51,52}. Perfluorooctane sulfonic acid (PFOS) and perfluorooctanoic acid (PFOA) are easily

absorbed through the gut. They bind to proteins and are distributed mainly to the blood 100 serum, kidney, and liver⁵³. Several PFAS have been measured in human umbilical cord 101 blood, indicating that they can cross the placenta^{54,55}. Zhan et *al*. demonstrated in 11 weeks 102 old male mice a marked change in the gut microbiota induced by PFOS⁵⁶. In a study by 103 104 Naspolini et al, infants born by caesarian section showed significant changes in their gut microbiota assessed in meconium associated with high exposures to PFAS⁵⁷. Thompson et 105 al. examined the effects of lifetime exposures to environmental contaminants on the 106 107 established adult microbiota and found that proximal exposures to perfluorohexane sulfonic acid (PFHxS) and PFOA at age 28 years appeared to be associated with measures 108 of microbiota diversity and taxonomic profiles⁵⁸. In 267 mothers and their one-month 109 infants from NoMIC cohort, Iszatt et al. observed that breast milk PFOS levels in 110 breastfeeding mothers was associated with decreased microbiota phylogenetic diversity 111 112 and specific richness, and that significant differences existed in community composition between groups with high and low PFOS exposure⁵⁹. 113

Given the antimicrobial properties of certain compounds of the phenol family (e.g., parabens and triclosan) and the results of these previous studies on triclosan^{41,42} (with a limited number of subjects) and on the most common PFAS^{57–59}, perturbations of one year child gut microbiota diversity and composition might be expected in relation with exposure to parabens, triclosan and certain PFAS. The objective of this study was to investigate the sensitivity of the gut microbiota at one year of age to specific phenols and PFAS.

120 Materials and Methods

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Design of SEPAGES couple-child cohort and data collection

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Study population

123 We relied on SEPAGES cohort (Suivi de l'Exposition à la Pollution Atmosphérique durant la Grossesse et Effet sur la Santé), a French couple-child cohort with detailed 124 monitoring of environmental exposures⁶⁰. The SEPAGES study population lives 125 approximately in a buffer of 80 km around the center of Grenoble, and includes urban, 126 127 peri-urban and rural zones. The SEPAGES cohort participants were pregnant women, their partner and future child. Pregnant women had to fulfil the following eligibility criteria: 128 being pregnant by less than 19 gestational weeks at inclusion, being older than 18 years, 129 having a singleton pregnancy, to be living in the study area and to plan to give birth in one 130 of the four maternity clinics from Grenoble area. Recruitment took place between July 131 132 2014 and July 2017 in eight obstetrical ultrasonography practices located in the Grenoble area. From the 484 families included in SEPAGES cohort, our study is restricted to 360 133 134 families with full outcome data. All required ethical and data privacy agreements 135 (including from CPP and CNIL) were obtained; all enrolled families signed an informed consent form. 136

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Biospecimens collection

Women collected samples from three micturitions per day during each follow-up week around 18 and 34 gestational weeks (median (25th–75th centiles) gestational age at urine collection: 18 weeks (16, 19) and 34 weeks (32, 35)), and around 2 months and 12 months (median (25th–75th centiles) child age at urine collection: 7 weeks (6, 9)) and 53 weeks (52, 55)), in plastic vials which composition did not include bisphenols. From the population of SEPAGES feasibility study, it was demonstrated that, when it comes to

estimating the effects of exposures averaged over windows of a week or more, collecting 145 three urine samples per day was not expected to entail bias, compared to a collection of all 146 daily urine samples, which is more cumbersome⁶¹. Women were asked to fill in a diary 147 indicating the hours of all collected micturitions and delay before putting the urine sample 148 in the freezer. After collection, samples were stored at -20°C at the house of the 149 participants. At the end of the follow-up week, samples were picked up by a study 150 fieldworker and brought to the certified biobank of Grenoble University hospital (bb-0033-151 152 00069), stored at -20°C until they were thawed at 4°C and pooled within-subject, withinperiod (pools of the same volume of each of the samples collected over a follow-up week). 153 These weekly pools were aliquoted and stored at -80°C. Maternal blood was collected at 154 home around the 18th gestational week (median (25th–75th centiles) gestational age at blood 155 collection: 18 weeks (16, 19)). 156

Parents from SEPAGES cohort were asked to collect fecal samples of their offspring in a sealed container (median ($25th-75^{th}$ centiles) child age at stool collection: 54 weeks (52, 55)). We focused on one year of age, a sensitive period when the microbiota undergoes rapid development^{62–64}. To ensure proper frozen conservation, samples were immediately stored at -20°C at the volunteer's home (for 1 to 7 days), transported on ice from the volunteer's home to the biobank where they were separated in three aliquots and stored at -80°C.

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Assessment of chemical exposures

All chemical analyses were performed at the Norwegian Institute of Public Health in Oslo (NIPH). Our focus here was on compounds of the chemical families of phenols and PFAS (Table S1). Because of their short half-life and the fact that they are mainly excreted in urine, phenols were assessed in urine samples of both SEPAGES mothers and children

collected during the second and third trimester of pregnancy, and post-natally at 2 and 12 170 months of age. Phenols were assessed in weekly pools after thawing by on-line solid phase 171 extraction with ultra-high-performance liquid chromatography and mass spectrometry⁶⁵. 172 While not formally accounting for urine dilution of individual samples, biomarker 173 174 concentrations assessed in such equal volume pools have shown to correlate well with those assessed in a pool of all urine samples collected over 24h or a week⁶⁶. PFAS were 175 determined in the serum samples collected around 18 gestational by high performance 176 liquid chromatography coupled with tandem mass spectrometry^{67,68}. PFAS have a strong 177 affinity for binding to serum proteins, such as albumin, which results in their distribution 178 mainly in serum, and less in milk⁶⁹ and urine⁷⁰, with urinary concentrations being less than 179 1% of those found in serum⁷¹. The choice of serum was justified by the reasons mentioned 180 above and by the fact that not all women breastfed. 181

182 Measurements below the limit of detection (LOD) and the limit of quantification (LOQ) were singly imputed using the compound's probability distribution⁷². We applied a 183 184 Neperian logarithmic transformation to the pollutant variables (ng/mL) to limit the 185 impact of high concentrations on our effect estimations. Compounds with more than 70% of observations below the limit of detection were categorized (2 categories: <LOD 186 and >LOD; or 3 categories <LOD, LOD-LOQ, >LOQ depending on the sample size in 187 188 each category). Compounds with more than 95% of observations below the limit of detection were not considered in our analyses (these were the following phenols: 189 bisphenols AF, B, F and triclocarban; and the following PFASs: perfluorotetradecanoic 190 acid (PFTeDa), perfluorobutanoic acid (PFBA), perfluoropentanoic acid (PFPeA), 191 sulfonic perfluorohexanoic acid (PFHxA), perfluorodecane acid (PFDS), 192 n-193 methylperfluorooctane sulfonamide (MeFOSA), n-ethylperfluorooctane sulfonamide (EtFOSA), 6:2 fluorotelomer phosphate monoester (6:2 PAP), 8:2 fluorotelomer phosphate 194

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195 monoester (8:2 PAP), perfluorooctyl phosphonic acid (PFOPA), perfluorodecyl196 phosphonic acid (PFDPA)).

Total and free forms of phenol concentrations were measured to evaluate potential 197 198 external contamination in a subset of 100 prenatal samples and in all the postnatal samples, since these samples were at higher risk of contamination (as urine was collected from 199 diapers). Contamination testing of phenol assays (by regressing the free against conjugated 200 forms of each compound) suggested no contamination for prenatal samples, while for 201 202 postnatal samples contamination was suspected for bisphenol A at 2 and 12 months, and methylparaben at 12 months⁷³. For these specific chemicals and exposure windows, 203 conjugated concentrations (obtained by subtracting the free form from the total) were used 204 205 for associations reported in the main analyses.

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Assessment of adjustment factors

From SEPAGES questionnaires, information on sociodemographic factors (including parental occupation), medical history, medical treatments, health events, active smoking during pregnancy, passive smoking exposure during pregnancy and postnatally, characteristics of the home (pet ownership) was collected. Mode of delivery, weight and height measurements performed by health care practitioners were copied from the child health booklet. Information on diet and food frequency were asked at 3, 6, 12, 18 and 36 months.

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- 216 Assessment of the gut microbiota
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Sequencing and data processing

Fecal samples (~150 mg) were aliquoted from 360 children at one year of age, a critical period for the development of the gut microbiota, particularly with the introduction

of solid food^{1,2}. Total DNA was extracted from all samples with the PowerFecal DNA 220 Isolation Kit (Qiagen), with a prior homogenization including chemical (incubation for 1h 221 222 at 70°C with guanidine thiocyanate and N-lauroyl-sarcosine 5%) and mechanical (beadbeating for 10 minutes) lysis steps. DNA quality and quantity were evaluated using a 223 spectrophotometer (Nanodrop 1000, Thermoscientific). The V3-V4 hypervariable region 224 of the 16S ribosomal RiboNucleic Acid (rRNA) gene was amplified with the following 225 341F-CCTACGGGNGGCWGCAG 226 primers: and 805R-GACTACHVGGGTATCTAATCC⁷⁴. Following quality control and sequencing library 227 construction, high-throughput sequencing was performed (MiSeq Illumina), the remaining 228 adapter/primer sequences were trimmed, and reads were checked for quality (≥ 20) and 229 length (≥ 200 bases) using cutadapt⁷⁵. Reads were further corrected for known sequencing 230 errors using SPAdes⁷⁶ and then merged using PEAR⁷⁷. Amplicons sequencing variants 231 (ASV) were identified using a Vsearch pipeline⁷⁸ set up to dereplicate, cluster and chimera 232 check the merged reads. ASV taxonomical classification was performed using a classifier 233 from the RDPTools suit⁷⁹. From the 360 stool samples collected at one year, we removed 4 234 235 samples which had a low DNA or sequencing quality (samples with number of reads below 2500). To control for variation in sequencing depth for diversity analyses, ASV matrix was 236 rarefied to 5,000 sequences, which led to the removal of 6 additional samples (n=350). To 237 238 see if our estimated richness matched the actual richness of the gut microbiota samples, we looked at rarefaction curves and counted the number of ASVs for a set of subsamples at 239 different sequencing depth thresholds. The number of ASVs detected increased and then 240 241 stabilized as the number of extracted sequences increased. The sequencing depth chosen for our analyses (5,000) was appropriate to observe a large number of ASVs excluding 242 243 only 6 samples (Figure S1). Taxa counts were converted to relative abundances (n=356). 350 and 356 children were available for the diversity analyses (see below), and taxonomyanalyses, respectively.

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Gut microbiota composition: α -diversity, β -diversity and taxonomy

248 α -diversity (i.e. diversity within a sample) was estimated using the specific249richness, Shannon diversity⁸⁰ and Faith's phylogenetic diversity indices⁸¹, on the rarefied250ASVs table (5,000 sequences) with R program version 4.2.2, package Phyloseq version2511.27.6⁸². β-diversity between each given pair of gut microbiota samples was calculated252using the Bray-Curtis dissimilarity metric⁸³, defined on the rarefied ASVs table (5,000253sequences).

Taxonomic affiliation was described at all taxa levels. Taxonomy analyses were conducted for the most abundant phyla and genera in our population. 16S rRNA gene sequencing is unable to differentiate *Shigella* species from *Escherichia coli* because of their nucleotide similarity. For this reason, genera *Escherichia* and *Shigella* were studied as a single taxon in all our analyses⁸⁴.

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260 Statistical analyses

We imputed missing values of adjustment covariates using simple imputation by predictive mean matching^{85,86}. Correlations between exposures, between exposures and covariates, and between gut microbiota parameters were assessed using Spearman's rank correlation coefficient. The directed acyclic graph presenting the assumed causal relations between covariates is given in Figure S2.

The parameters of gut microbiota considered in relation to exposures were the three above-mentioned indices of α -diversity, the Bray-Curtis β -diversity metric, the 4 most abundant phyla and the 46 genera detected in at least 30% of the children.

Regarding specifically α -diversity analyses, we relied first on single-pollutant 269 approaches using multiple linear regression (one model per exposure and outcome) 270 adjusted for a priori identified covariates: analytic batch effect (MiSeq 16S rRNA gene 271 272 sequencing run), child age at feces collection, delivery mode, gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one 273 year), period of introduction of solid food, breast-feeding status up to 48 weeks, antibiotics 274 275 use during the first year of life, presence of pets at home, passive smoking during the first 276 year of life, and maternal characteristics (parity, age and body mass index (BMI) before 277 pregnancy, education, and smoking status during pregnancy).

Regarding β-diversity analyses, we investigated group differences in Bray-Curtis β-278 diversity for low (1st tertile or <LOD), medium (2nd tertile or LOD-LOO), and high (3rd 279 tertile or >LOQ) levels of exposure considered separately at each time window (one model 280 281 per exposure) by testing significance of pairwise groups of exposure with Permutational Multivariate Analysis of Variance Using Distance Matrices (PERMANOVA), using R 282 program version 4.2.2, package Vegan version 2.6-4, Adonis2 function⁸⁷. For a sub-group 283 of pollutants for which within-group β-diversity was significantly different from the inter-284 285 group diversity, we performed further analyses to identify if the observed difference was 286 between the low and medium exposure groups, between the low and high exposure groups, or between the medium and high exposure groups, using R program version 4.2.2, package 287 pairwiseAdonis, pairwise.adonis2 function⁸⁸. β-diversity analyses were adjusted for the 288 289 same covariates as the α -diversity analyses.

To limit associations due to multiple comparisons, a family-wise error rate (FWER) correction to the p-value significance threshold was applied for the single-pollutants models (α - and β -diversity) for pollutants without *a priori* known antimicrobial properties (i.e., bisphenols A and S, benzophenone 3 and the PFAS). The correction used a

Bonferroni procedure extended to handle correlated tests: the actual number of associations 294 being tested (T) is replaced by a smaller value, the effective number of independent tests 295 (Te). Te was estimated by the effective number of independent exposures $\sum_{i=1}^{M} [I(\lambda_i > \lambda_i)]$ 296 1) $(\lambda_i - 1)$] multiplied by the effective number of independent outcomes $\sum_{i=1}^{N} [I(\lambda_i > 1)]$ 297 1) $(\lambda_i - 1)$], where I(x) is an indicator function and λ_i are the eigenvalues of the matrix of 298 correlations between M exposures and the eigenvalues of the matrix of correlations 299 300 between N outcomes. The p-value threshold to control FWER to α (in our case, 5%), using Te in a Bonferroni procedure, is then α / Te (adapted from⁸⁹). For the main diversity 301 302 analysis, the 27 time window-specific exposure corresponded to 17 independent predictors 303 and the 4 α - and β -diversity indices to 3 independent outcomes. The corrected significance level was thus 0.05/(17x3) = 0.001. No such correction was applied to the regression 304 models corresponding to compounds with a priori known antimicrobial properties (i.e. 305 parabens and triclosan). 306

307 To identify any mixture effect of multiple pollutant exposures on α -diversity indices, we first used multiple linear regressions models including all exposures assessed at 308 309 the same time window. Then, for continuous exposure variables only, we implemented BKMR, a statistical approach for analyzing multipollutant mixtures⁹⁰, adjusted for the 310 311 same covariates as for the single-pollutant regression models, and using R program version 4.2.2, package bkmr version 0.2.2. The cumulative effects of the mixtures were assessed 312 313 by estimating the expected change in indices of α -diversity associated with concurrent changes in all of the components of the mixture from their 25th percentile levels. The 314 estimated effect of an increase from the 25th to 75th percentile in a single pollutant level on 315 α -diversity indices when all other pollutant levels are fixed at either the 25th, 50th, or 75th 316 percentiles were also investigated, with the aim to identify the most important contributors 317 318 of the mixture.

Then, we investigated associations between exposures and the gut microbiota 319 taxonomy at one year. We performed independent linear regression models using the 4 320 321 most abundant phyla and the 46 genera detected in at least 30% of the children as 322 explained variables, and each of the exposure as explanatory log-transformed continuous 323 variables. These taxonomy analyses were adjusted for the same covariates as the diversity analysis. Null values in genera variables were replaced by the value 1/5000 before the 324 variables were log-transformed. We applied a FWER multiple comparison correction for 325 326 all associations between bacterial genera and pollutants (with and without known antimicrobial properties). The 47 time window-specific exposure corresponded to 29 327 independent predictors and the 46 genera detected in at least 30% of the children to 31 328 independent outcomes. The corrected significance level was thus $0.05/(29x31) = 5.6x10^{-5}$. 329

As sensitivity analyses, we repeated the α -diversity analyses using two different 330 331 thresholds of rarefaction (5,000 and 10,000 reads). Postnatal samples contamination was suspected for bisphenol A at 2 and 12 months, and methylparaben at 12 months⁷³; for 332 333 these specific chemicals and exposure windows, conjugated concentrations were used for 334 associations reported in the main analyses, while associations with total and free concentrations were reported in the sensitivity analyses. Finally, we repeated our analyses 335 for perfluoroheptanesulfonic acid (PFHpS), PFHxS and PFOS exposures during the second 336 337 trimester of pregnancy excluding one mother with very high concentrations.

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All statistical analyses were performed with R program version 4.2.2.

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340 **Results**

341 Study population

342 Out of 484 families participating in SEPAGES cohort, 356 had available 343 exposure and microbiota data, on which we focused. These women were highly

educated (95% had an undergraduate or graduate degree) and 94% of them did not 344 smoke during pregnancy. Most of them (76%) had a body mass index (BMI) between 345 18.5 and 25 kg/m² ⁶⁰. No significant difference existed between SEPAGES pregnant 346 women included in the microbiota analyses and those excluded (Table S2). The 347 proportion of SEPAGES children with a weight at birth under 2.5 kg was 4.2%; 8.4% of 348 children were not breastfed at birth, while 23% were still breastfed at 48 weeks. 349 SEPAGES children were more often full-term deliveries compared to children from 350 351 France and tended to have a higher birth weight and height. No significant difference in the considered characteristics was observed between SEPAGES children included in the 352 353 microbiota analyses and those excluded (Table S3).

Comparisons of exposures between the 356 mothers and children included and 354 those excluded are given Table S4. Compared to excluded mothers, mothers who were 355 356 included in this study had lower concentrations of second and third trimester propylparaben and butylparaben and PFOA, 357 second trimester and higher 358 perfluorotridecanoic acid (PFTrDa) and perfluorobutanesulfonic acid (PFBS) (p<0.05). Pearson correlations between exposures at various exposure windows are given Figure S3. 359 Exposures to certain PFAS during the second trimester of pregnancy were correlated. 360 Perfluorononanoic acid (PFNA) was correlated with perfluorodecanoic acid (PFDA) 361 362 (r=0.8, p<0.001) and PFOA (r=0.8, p<0.001), and PFOS was correlated with PFHxS (r=0.8, p<0.001) and perfluoroheptane sulfonic acid (PFHpS) (r=0.9, p<0.001). Child 363 exposures to methyl- and propylparaben at one year of age were also strongly correlated 364 (r=0.9, p<0.001). Correlations of exposures across exposure windows were generally very 365 low. Perinatal exposures to phenols and PFAS were not strongly associated with most 366 367 covariates, with the exception of PFAS levels that tended to decrease with parity (Figure 368 S4).

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The distribution of α -diversity indices and of the most abundant phyla and genera in the gut microbiota is given Table S5 and Figures 1a and 1b.

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Relations between maternal and child characteristics and gut microbiota

Associations of maternal and child characteristics with the gut microbiota α diversity are presented in Table S6. Child passive smoking during the first year of life was associated with a lower specific richness index and a lower Faith's phylogenetic index. Birth length was positively associated with all three α -diversity indices. Antibiotics use during the first year of life tended to be associated with a decreased specific richness. None of the other characteristics were associated with α -diversity at the (uncorrected) 5% level.

Associations of maternal and child characteristics with the 4 main phyla are given in Table S7. Boys tended to have fewer Actinobacteria, compared to girls. Maternal active smoking during pregnancy was associated with fewer Bacteroidetes. A longer gestational duration was associated with fewer Actinobacteria and more Bacteroidetes.

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384 Relations between chemical exposures and gut microbiota diversity

385 *α*-diversity

The number of children included in the single-pollutant analysis varied between 386 334 and 356, depending on the availability of the exposure data. When we considered 387 associations with the strongest a priori hypothesis (corresponding to pollutants with a 388 priori known antimicrobial properties, i.e., triclosan and parabens), which were therefore 389 390 not corrected for multiple testing, child butylparaben concentration at two months was associated with increased specific richness, Shannon diversity index and Faith 391 392 phylogenetic diversity (p-values: 0.03, 0.04 and 0.04 respectively, Table 1 and Figure 2) 393 and there were suggestive associations with ethylparaben concentration during the third

394 pregnancy trimester and propylparaben concentration at 12 months. The point estimates of 395 these associations with butylparaben concentrations at two months were only weakly 396 attenuated in multiple linear regression models simultaneously adjusted for co-exposures 397 (Table S10; see also Table S8, Table S9 and Table S11 for analyses co-adjusted for all 398 exposures at the other exposure windows).

Regarding compounds without *a priori* known antimicrobial properties (i.e., other phenols and PFAS), for which a multiple comparison correction was applied, there was no clear evidence in favor of associations (Table 2 and Figure S5). The strongest associations (in terms of p-value) were observed with bisphenol S levels assessed in 2-month children.

When we investigated a possible mixture effect on the α -diversity indices using 403 404 Bayesian kernel machine regression (BKMR) model (313 children with full exposure and α -diversity data assessment, Figure 3 and Figure S6), Shannon diversity index tended to 405 406 increase with increased exposure to the mixture. The estimated effects of an increase from the 25^{th} to 75^{th} percentile in a single biomarker concentration on α -diversity indices when 407 408 all other biomarkers' concentrations were fixed did not permit to identify one or several 409 important contributors to the mixture effect (Figure S6). No clear associations were observed for the specific richness and the Faith phylogenetic diversity (Figure 3). 410

411

412 β-diversity

For each pollutant, we tested whether children gut microbiota exposed to "low" (1st tertile or <LOD), "medium" (2nd tertile or between LOD and LOQ) or relatively "high" (3rd tertile or >LOQ) concentrations were more or less similar based on β -diversity distance (Bray-Curtis dissimilarity index), using permutational multivariate analysis of variance (PERMANOVA) to test significance, with FWER correction for multiple testing in the case of compounds without strong *a priori* evidence of antimicrobial properties. For

pollutants with a priori known antimicrobial properties, there were significant differences 419 in community composition in association with methylparaben and propylparaben levels at 420 421 12 months (p-values: 0.03 and 0.008 respectively, Table 3), with greater dissimilarity 422 between the low and high exposure tertiles (p-values: 0.03 and 0.002 respectively, Figure 4). For pollutants without a priori known antimicrobial properties, no association passed 423 the threshold corrected for multiple testing (p-value<0.001). Analyses not corrected for 424 multiple testing suggested differences in community composition in relation with 425 426 benzophenone 3 exposure levels at 2 months (p-value: 0.03, Table 4).

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428 **Relations between phenols and gut microbiota taxonomy**

429 **Phylum level**

430 Spearman correlations between the relative abundances of the 4 most abundant431 phyla are given Figure S7.

In an attempt to explain the above-mentioned associations of parabens with 432 433 diversity, we studied associations between pollutants associated with α - and β -diversity and the four most abundant phyla (Table 5). Child concentrations of methylparaben and 434 propylparaben at 12 months were associated with decreased relative abundance of phylum 435 Proteobacteria (p-values: 0.01 and 0.02, respectively). Maternal exposure to ethylparaben 436 during the third pregnancy trimester was associated with increased abundance of phylum 437 438 Firmicutes (p-value: 0.04). Child exposure to butylparaben at 2 months was not associated with any disturbance of the phyla studied. Regarding the pollutants not associated with 439 440 perturbations in α - or β -diversity, associations with the 4 most abundant phyla are given for exploratory purposes in Table S12. 441

442

443 Genus level

19

46 of the 192 genera present in the children gut microbiota at one year of age were 444 detected in at least 30% of children. None of the associations between these 46 genera and 445 the 47 exposure variables passed the threshold corrected for multiple testing (p-446 value $< 5.6 \times 10^{-5}$). Among the strongest associations (p-value< 0.0035), exposure to 447 methylparaben at 12 months tended to be associated with an increase in Lachnospiracea 448 incertae sedis (p-value: 0.003); exposure to ethylparaben during the second trimester of 449 450 pregnancy tended to be associated with an increase in *Enterococcus* (p-value: 0.002) while 451 ethylparaben at 12 months tended to be associated with a decrease in Enterobacter and Klebsiella (p-values: 0.0004 and 0.0006, respectively); exposure to propylparaben during 452 453 the second trimester of pregnancy tended to be associated with a decrease in Anaerostipes (p-value: 0.002); exposure to butylparaben at 12 months tended to be associated with an 454 455 increase in Lachnospiracea incertae sedis and Anaerotruncus (p-values: 0.0002 and 0.001, 456 respectively) and a decrease in Enterococcus genus (p-value: 0.0008); exposure to bisphenol A at 12 months tended to be associated with an increase in Clostridium XVIII 457 458 and Coproccocus (p-values: 0.003 and 0.002, respectively); bisphenol S exposure at 2 459 months tended to be associated with an increase in Collinsella and a decrease in Romboutsia (p-values: 0.0002 and 0.002, respectively); finally, exposure to benzophenone 460 3 during the second trimester of pregnancy tended to be associated with a decrease in 461 Romboutsia and Clostridium XIVa (p-values: 0.002 and 0.003, respectively), while 462 exposure to benzophenone 3 at 2 months tended to be associated with a decrease in the 463 taxon grouping genera Escherichia and Shigella (p-value: 0.001). The p-values and the 464 465 direction of the associations according to bacterial genus and exposure are shown Figure 5. Beta values of the strongest associations (p-value<0.0035) with their confidence intervals 466 467 are given Figure 6, while all associations with the genera analyses are shown in Table S13.

468

469 Sensitivity analyses

Using two different thresholds (5,000 and 10,000) of rarefaction to define α -470 471 diversity did not strongly influence our results (Table S14). We tested different qualitative and quantitative α -diversity indices, with results qualitatively similar to those obtained 472 with specific richness, Shannon α -diversity, and Faith's phylogenetic diversity indices. 473 Associations using 12 months total and free methylparaben concentrations and 2- and 12-474 month total and free bisphenol A concentrations are reported in Table S15. Estimated 475 476 effects of PFHpS, PFHxS and PFOS exposures during the second trimester of pregnancy excluding one mother with very high concentrations of these three compounds are given in 477 Table S16. The exclusion of this subject resulted in stronger associations between exposure 478 479 to PFHxS during the second trimester of pregnancy and Shannon diversity index, and between exposure to each of these three PFAS and the abundance of phylum 480 481 Proteobacteria (Table S16). Finally, adjusting associations between phenols exposures and the gut microbiota composition for specific gravity measured in urine samples did not 482 483 strongly influence our results (Table S17).

484 **Discussion**

In our couple-child cohort of 356 families, perinatal exposure to certain parabens, which have *a priori* known antimicrobial properties, tended to be associated with perturbations in α - and β -diversity in one year child gut microbiota. These parabens were also associated with changes in the abundances of specific phyla and genera.

489

490 In our study, most of the associations observed between maternal and child characteristics (leaving chemical factors aside) with child gut microbiota were in 491 492 agreement with the literature. As expected, vaginal delivery was associated with increased Shannon diversity⁹¹. Maternal and infant exposure to tobacco, and antibiotic use during the 493 first year of life are known to alter the gut microbiota^{92,93} and they were associated with 494 495 decreases of specific α -diversity measures or alteration of certain phyla abundances. 496 Longer gestation duration was associated with increased abundance of Bacteroidetes, and with decreased abundance of Actinobacteria. As reviewed by Kumbhare et al., preterm 497 498 infants show high levels of facultative anaerobes and lower levels of strict anaerobes like *Bacteroides* when compared with term infants⁹⁴. 499

500 Maternal distant exposure to a compound with antimicrobial properties (ethylparaben in the third trimester of pregnancy) tended to be associated with a decrease 501 502 in α -diversity at one year (specific richness and Faith phylogenetic diversity), whereas 503 more recent exposure of the newborn to these antimicrobial compounds (propylparaben at 504 12 months, butylparaben at 2 months) was associated with an increase in α -diversity indices (Shannon diversity and the three diversity indices, respectively). Parabens are 505 506 postulated to exert their antimicrobial properties by disrupting membrane transport processes or by inhibiting synthesis of DNA and RNA or of some key enzymes, such as 507 ATPases and phosphotransferases, in some bacterial species⁹⁵. Perinatal exposure to 508

triclosan, for which we expected an effect because of its antimicrobial properties^{96–98}, 509 showed no evidence of association with gut microbiota α -diversity, and this was also the 510 511 case for the other pollutants of the phenol and PFAS families considered (after correction for multiple comparisons). A few of the exposures studied were highly correlated, 512 513 including child exposures to certain parabens at one year of age, and certain PFAS exposures during the second trimester of pregnancy (Figure S3). The BKMR mixture 514 analysis showed that increased exposure to the mixture of chemicals considered tended to 515 516 increase Shannon diversity but did not permit to identify the most important contributors of the mixture. A higher α -diversity in infancy indicates a more mature, adult-like 517 community. It has been hypothesized that functional redundancy provided by a highly 518 diverse microbiota may allow better responses to environmental fluctuations, promoting 519 intestinal homeostasis and maintaining human health⁹³. However, the idea that a high α -520 diversity is always beneficial for health in children has been questioned⁹⁹, especially 521 considering that certain diseases, such as autism spectrum disorders, have been associated 522 with increased α -diversity^{100,101}. 523

524 To our knowledge, there is no previous study on the effects of ethyl-, propyl- and butyl-parabens on the diversity of the human gut microbiota. Two toxicological studies 525 have investigated the effects of methylparaben on the diversity of the gut microbiota in 526 527 animal models: Hu et al. described that oral methylparaben exposure (0.105 mg/kg/day) 528 did not change the α -diversity at any time point but resulted in significant changes in the overall bacterial composition (β -diversity) and in taxonomy in adolescent rats at postnatal 529 day 62⁴⁰ coherently with our results. In another study, methylparaben exposure at 530 environmentally realistic concentrations (1 and 10 µg/L) was capable of driving gut 531 532 microbiota of zebrafish to dysbiosis. Particularly in female intestine, methylparaben

exposure led to a significant increase in diversity of gut microbiota measured directly after
exposure¹⁰².

In a second tier, we investigated if the compounds associated with changes in α - or β -diversity were associated with perturbations in the gut microbiota phyla at one year. In the study of Hu et *al.*, relative abundance of phylum Proteobacteria was increased in methylparaben-treated rats compared to controls⁴⁰, contrary to our results. Then, to provide a broader vision, we extended the phyla analyses to all pollutants whatever their associations with α - or β -diversity (Table S12). Many of the compounds tested were associated with a decrease in the abundance of Proteobacteria.

Finally, as an exploratory analysis, we investigated the relation between each of the 542 543 exposures and the relative abundance of the 46 most abundant genera (detected in at least 30% of the children). None of the associations passed the threshold corrected for multiple 544 comparison (p-value $< 5.6 \times 10^{-5}$), in a context of a large number of associations tested. The 545 546 strongest associations (p-value<0.0035) may be worth discussing. These associations were between genera belonging to 3 phyla, which were Firmicutes, Actinobacteria, and 547 548 Proteobacteria, and mainly postnatal exposures from the phenol family. None of the 549 exposures to PFAS or triclosan were strongly associated with bacterial genera. Perinatal exposures (bisphenol A, methyl-, ethyl- and butyl-parabens at 12 months, propylparaben 550 551 and benzophenone 3 during the second trimester of pregnancy, benzophenone 3 at 2 months) showed effects on genera belonging to the family Lachnospiraceae (increases of 552 553 genera Clostridium XVIII, Coprococcus and Lachnospiracea incertae sedis and decreases of genera Anaerostipes and Clostridium XlVa) and the Enterobacteriaceae (decreases in 554 555 the taxon grouping genera Escherichia and Shigella, and of genera Enterobacter and Klebsiella). Some toxicological studies on animal models also suggested an association 556 between bisphenol A exposure and an increase in *Lachnospiraceae* taxa^{46,103,104} similarly 557

to the trend observed in our study, while another found the opposite association¹⁰⁵. *Coprococcus comes* was increased in bisphenol A exposed mice compared with control mice in the study by Lai et al ⁴⁷, similarly to the trend observed in our study at the genus level. To our knowledge, no other study investigated the effects of phenol exposures on the gut microbiota, either in toxicology or epidemiology.

The clinical features associated with early life gut dysbiosis may include, among 563 emergence of antimicrobial resistance¹⁰⁶, autoimmunity^{107,108} 564 others, the and neurocognitive developmental problems^{109,110}. Members of Lachnospiraceae family are 565 among the main producers of short-chain fatty acids, and therefore play an important role 566 in host physiology¹¹¹, but different taxa from this family were also associated with 567 different intra- and extraintestinal diseases. For example, Lachnospiracea incertae sedis 568 was higher in children with autism spectrum disorders and attention deficit hyperactivity 569 disorders compared to neurotypical children in 2 case-control studies^{112,113}. In an 570 prospective study, Laue et al. found that higher relative abundance of Coprococcus in the 571 572 gut microbiota of children at 2 years was associated with poorer social behaviors at 3 years of age^{114} . 573

Previous studies have shown that the gut microbiota develops intensively in the first 574 years of life in relation to the development of the central nervous system^{115–117} and that it is 575 576 needed to prime the innate immune system in both the periphery and central nervous system¹¹⁸. Clarke et al. showed that peptidoglycan from commensal bacteria primes the 577 innate immune system. The pattern recognition receptor Nod1, which recognizes meso-578 579 diaminopimelic acid containing peptidoglycan found predominantly in gram-negative bacteria, was identified as the homeostatic regulator mediating the systemic effects of 580 peptidoglycan¹¹⁹. As confirmed by our study, gram-negative bacteria from the 581 Proteobacteria phylum, such as Escherichia and Shigella, are among the most abundant 582

microbes during the first year of life¹. *Escherichia* and/or *Shigella* genera were decreased in the gut microbiota of autistic children compared to neurotypical children in 3 casecontrol studies^{112,120,121}, but increased in another one¹²². Together, these results suggest that the components found in bacteria from *Escherichia* and *Shigella* genera may play a role in priming the host immune system during infancy, and in the long-term programming of central nervous system and behavior, and that an early decrease in these bacteria in childhood could have consequences on the development of the child.

590

Our study is the first to present results on the impact of perinatal exposure to 591 widespread chemicals on the gut microbiota of one-year children. It is based on a 592 prospective couple child cohort including 360 families with child microbiota assessment, 593 with rich questionnaire data to assess potential confounders and extensive exposure 594 595 assessment of two families of pollutants (phenols and PFAS) measured in urine and serum. 596 The assessment of chemical exposures during four perinatal time windows enabled a 597 unique and precise evaluation of exposures during critical developmental periods. DNA 598 was extracted from fecal samples using a technique that has been proven to allow an accurate representation of the overall microbial community (validated by the 599 600 Metagenomics of the Human Intestinal Tract project and International Human Microbiome Standards^{123–125}). For short half-life chemicals with high intra-individual variability, such 601 602 as the synthetic phenols studied in this work, the four urine collection weeks we relied on has shown, for a given sample size, to strongly decrease bias in the effect estimates and 603 increase power, compared with studies relying on one urine sample per subject^{61,126}. 604

In spite of the relatively large sample size compared to the existing literature, our power was probably low, in particular for the compounds with low *a priori* likelihood of an effect, for which we applied a multiple testing correction procedure. Also, despite the

fact that the analyses were adjusted for potential confounders, residual confounding factors 608 cannot be excluded. Exposure to toxicants other than phenols and PFAS, has not been 609 610 considered in this study. However, other studies suggested that biomarkers of exposure to phenols are not or weakly correlated with pollutants from other chemical families^{127,128}, 611 612 limiting the potential for residual confounding by co-exposures. Finally, cross-sectional 613 associations with 1 year chemical exposures and 1 year child gut microbiota should be interpreted with caution, as gut microbiota may influence xenobiotic metabolism¹²⁹, hence 614 615 to a risk of reverse causality.

616

Perinatal exposure to certain parabens possibly influences the diversity of the gut 617 618 microbiota in early childhood. Methyl-, ethyl- and propyl-paraben exposures were also 619 associated with the abundance of phyla Firmicutes and Proteobacteria. Perinatal exposures 620 to certain parabens were also associated with the taxonomy at the genus level, particularly genera belonging to the families Lachnospiraceae and Enterobacteriaceae, but these 621 622 associations were not maintained after correction for multiple testing. Studies on even 623 larger sample sizes should be conducted to confirm these results and assess whether associations are maintained in childhood. 624

625 Abbreviations

- 626 ASVs: Amplicon Sequence Variants
- 627 BMI: Body Mass Index
- 628 BKMR: Bayesian kernel machine regression
- 629 CNIL: Commission Nationale de l'Informatique et des Libertés
- 630 CPP: Comité de Protection des Personnes
- 631 DNA: DeoxyriboNucleic Acid
- 632 EtFOSA: n-ethylperfluorooctane sulfonamide
- 633 FOSAs: fluorooctane sulfonamides
- 634 FWER: family-wise error rate
- 635 GUMME: Gut Microbiota in early childhood and Maternal Environmental exposures
- 636 MeFOSA: n-methylperfluorooctane sulfonamide
- 637 NIPH: Norwegian Institute of Public Health
- 638 PFAS: poly- and perfluoroalkyl substances
- 639 PFBA: perfluorobutanoic acid
- 640 PFBS: perfluorobutanesulfonic acid
- 641 PFCAs: perfluoroalkyl carboxylates
- 642 PFDA: perfluorodecanoic acid
- 643 PFDoDa: perfluorododecanoic acid
- 644 PFDPA: perfluorodecyl phosphonic acid
- 645 PFDS: perfluorodecane sulfonic acid
- 646 PFHpA: perfluoroheptanoic acid
- 647 PFHpS: perfluoroheptanesulfonic acid
- 648 PFHxA: perfluorohexanoic acid
- 649 PFHxPA: perfluorohexylphosphonic acid

- 650 PFHxS: perfluorohexanesulfonic acid
- 651 PFNA: perfluorononanoic acid
- 652 PFOA: perfluorooctanoic acid
- 653 PFOPA: perfluorooctyl phosphonic acid
- 654 PFOS: perfluorooctane sulfonic acid
- 655 PFOSA: perfluorooctane sulfonamide
- 656 PFPeA: perfluoropentanoate
- 657 PFSAs: perfluoroalkyl sulfonates
- 658 PFUnDA: perfluoroundecanoic acid
- 659 PFTeDa: perfluorotetradecanoic acid
- 660 PFTrDa: perfluorotridecanoic acid
- 661 rRNA: ribosomal RiboNucleic Acid
- 662 SEPAGES cohort: Suivi de l'Exposition à la Pollution Atmosphérique durant la Grossesse
- 663 et Effet sur la Santé
- 664 6:2 diPAP: 6:2 fluorotelomer phosphate diester
- 665 6:2 PAP: 6:2 fluorotelomer phosphate monoester
- 666 8:2 diPAP: 8:2 fluorotelomer phosphate diester
- 667 8:2 PAP: 8:2 fluorotelomer phosphate monoester

668 Supporting Information

- Table S1: Assessment of exposure to phenols and perfluoroalkyl substances in SEPAGES cohort.
- 670 Table S2: Description of pregnant women from SEPAGES cohort and comparison with women671 from Grenoble and France.
- Table S3: Description of children from SEPAGES cohort, and comparison with children fromGrenoble and France.
- Table S4: Distribution and comparison of chemical exposures in SEPAGES cohort (484 mother-child pairs).
- Table S5: Distribution of α-diversity and major taxa in one year child gut microbiota from
 SEPAGES cohort.
- Table S6: Influence of maternal and child characteristics on the gut microbiota diversity in one-year SEPAGES children.
- Table S7: Influence of the maternal and child characteristics on the gut microbiota most abundantphyla in one-year SEPAGES children.
- Table S8: Associations between concentrations of pollutants during the second trimester of pregnancy and the α -diversity of the child gut microbiota at one year (single-pollutant models and multiple linear regression models adjusted for all mentioned exposures assessed during the second trimester of pregnancy, n = 333 mother-child pairs in all models).
- Table S9: Associations between concentrations of pollutants during the third trimester of pregnancy and the α -diversity of the child gut microbiota at one year (single-pollutant models and multiple linear regression models adjusted for all mentioned exposures assessed during the third trimester of pregnancy, n = 344 mother-child pairs in all models).
- 690 Table S10: Associations between concentrations of pollutants at two months and the α -diversity of
- 691 the child gut microbiota at one year (single-pollutant models and multiple linear regression models
- 692 adjusted for all mentioned exposures assessed in two-month old children, n = 338 mother-child 693 pairs in all models).
- Table S11: Associations between concentrations of pollutants at twelve months and the α-diversity of the child gut microbiota at one year (single-pollutant models and multiple linear regression

- 696 models adjusted for all mentioned exposures assessed in one-year old children, n = 345 mother-697 child pairs in all models).
- 698 Table S12: Adjusted associations between concentrations of pollutants without identified effects on
- 699 α -diversity or β -diversity and the 4 most abundant phyla in one-year children gut microbiota (n
- between 340 and 355 mother-child pairs).
- 701 Table S13: Adjusted associations between concentrations of pollutants and the 46 most abundant
- genera in one-year children gut microbiota (n between 340 and 355 mother-child pairs).
- Table S14: Adjusted associations between chemical exposures and the gut microbiota α -diversity at
- 704 different sequencing depths.
- Table S15: Adjusted associations between phenol assays suspected of contamination and one yearchild gut microbiota composition.
- Table S16: Adjusted associations between PFHpS, PFHxS and PFOS and gut microbiotacomposition, before and after exclusion of one outlier.
- Table S17: Adjusted associations between phenols exposures and the gut microbiota composition
- 710 before and after adjustment for specific gravity.
- 711
- Figure S1: Observed ASVs regarding the depth of sequencing in one-year child gut microbiotafrom SEPAGES cohort.
- Figure S2: Direct acyclic graph of the relation between chemical exposures and one year child gutmicrobiota.
- 716 Figure S3: Pearson correlations between chemicals assessed during various exposure windows.
- 717 Figure S4: Spearman correlations between chemicals and covariates.
- 718 Figure S5: Associations between concentrations of pollutants without a priori known antimicrobial
- properties and the α -diversity of the child gut microbiota at one year (adjusted single-pollutant
- models, n between 334 and 349 mother-child pairs).
- Figure S6: Estimated effect of an increase from the 25th to 75th percentile in a single biomarker
- concentration on α -diversity indices when all other biomarkers are fixed at either the 25th, 50th, or
- 723 75^{th} percentiles (mixture models, n = 313 mother-child pairs).

- 724 Figure S7: Spearman correlations between the most abundant taxa in the gut microbiota of
- 725 SEPAGES children.

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750 SEPAGES biospecimens are stored at Grenoble University Hospital (CHU-GA) biobank

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1239 Tables

1240 Table 1: Adjusted associations between concentrations of pollutants with a priori known antimicrobial properties (parabens, triclosan) and the

1241 α -diversity of the child gut microbiota at one year (n between 334 and 349 mother-child pairs).

			Specific richnes	s	1	Shannon diversit	у	Faith's phylogenetic diversity		
Chemical and exposure window	\mathbf{N}^{I}	Beta ²	95% CI ³	p-value	Beta ²	95% CI ³	p-value	Beta ²	95% CI ³	p-value
Methylparaben				•			•			•
Mother, pregnancy trim. 2	349	-0.5	-3, 2	0.50	0.02	-0.02, 0.07	0.26	-1	-7, 4	0.63
Mother, pregnancy trim. 3	344	-0.7	-2, 0.8	0.32	0.02	-0.01, 0.05	0.15	-2	-7, 2	0.27
Child, 2 months	338	0.6	-0.4, 2	0.21	0	-0.02, 0.02	0.99	1	-2, 4	0.39
Child, 12 months	345	0.7	-0.6, 2	0.26	0.02	-0.01, 0.05	0.14	2	-2, 6	0.25
Ethylparaben										
Mother, pregnancy trim. 2	349	-1	-3, 0.5	0.13	0	-0.04, 0.04	0.92	-4	-10, 2	0.18
Mother, pregnancy trim. 3	344	-2	-4, 0.1	0.06	0.02	-0.03, 0.06	0.42	-6	-12, 0.5	0.07
Child, 2 months				0.18			0.14			0.24
<loq< td=""><td>115 (34%)</td><td>_</td><td>_</td><td></td><td></td><td></td><td></td><td></td><td>_</td><td></td></loq<>	115 (34%)	_	_						_	
>LOQ	223 (66%)	4	-2, 11		0.1	-0.03, 0.23		11	-7, 29	
Child,12 months	345	0.3	-1, 2	0.52	0.01	-0.02, 0.03	0.61	0.9	-3, 5	0.62
Propylparaben										
Mother, pregnancy trim. 2	349	-0.3	-1, 0.8	0.47	0	-0.02, 0.02	0.97	-2	-5, 2	0.34
Mother, pregnancy trim. 3	344	-0.5	-1, 0.5	0.27	0.01	-0.01, 0.02	0.59	-2	-5, 0.9	0.19
Child, 2 months				0.26			0.35			0.49
<lod< td=""><td>125 (37%)</td><td>_</td><td>_</td><td></td><td>—</td><td>_</td><td></td><td>—</td><td>—</td><td></td></lod<>	125 (37%)	_	_		—	_		—	—	
>LOD	213 (63%)	3	-3, 10		0.06	-0.07, 0.19		6	-12, 24	
Child, 12 months	345	0.5	-0.6, 1	0.32	0.02	0.00, 0.04	0.06	1	-1, 4	0.34
Butylparaben										
Mother, pregnancy trim. 2				0.15			0.41			0.12
<lod< td=""><td>274 (79%)</td><td>_</td><td>_</td><td></td><td>—</td><td>_</td><td></td><td>—</td><td>—</td><td></td></lod<>	274 (79%)	_	_		—	_		—	—	
LOD-LOQ	44 (13%)	-7	-16, 2	0.13	-0.06	-0.25, 0.13	0.51	-23	-49, 2	0.07
>LOQ	31 (8.9%)	-7	-17, 3	0.18	-0.14	-0.35, 0.08	0.21	-19	-48, 10	0.19
Mother, pregnancy trim. 3				0.11			0.98			0.10
<lod< td=""><td>277 (81%)</td><td>_</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></lod<>	277 (81%)	_								
LOD-LOQ	37 (11%)	-8	-17, 2	0.10	-0.01	-0.20, 0.18	0.91	-23	-50, 3	0.09
>LOQ	30 (8.7%)	-7	-18, 3	0.16	-0.02	-0.23, 0.19	0.86	-21	-50, 8	0.15
Child, 2 months				0.03			0.04			0.04
<lod< td=""><td>265 (78%)</td><td>_</td><td>_</td><td></td><td></td><td></td><td></td><td></td><td>_</td><td></td></lod<>	265 (78%)	_	_						_	

>LOD	73 (22%)	8	0.6, 15		0.15	0.00, 0.30		22	1,42	
Child, 12 months				0.20			0.29			0.25
<lod< td=""><td>221 (64%)</td><td>_</td><td>—</td><td></td><td>—</td><td>_</td><td></td><td>_</td><td>—</td><td></td></lod<>	221 (64%)	_	—		—	_		_	—	
LOD-LOQ	35 (10%)	4	-6, 14	0.46	0.03	-0.18, 0.24	0.76	11	-17, 39	0.44
>LOQ	89 (26%)	6	-1, 13	0.10	0.12	-0.03, 0.26	0.12	16	-4, 36	0.11
Triclosan										
Mother, pregnancy trim. 2	349	0	-1, 1	0.63	-0.01	-0.04, 0.03	0.74	0.1	-4, 4	0.97
Mother, pregnancy trim. 3	344	0.1	-1, 2	0.62	0.01	-0.01, 0.04	0.33	0.5	-4, 5	0.82
Child, 2 months	338	2	-1,4	0.20	0.03	-0.02, 0.08	0.27	5	-2, 12	0.19
Child, 12 months	345	0.8	-2, 3	0.42	0.02	-0.04, 0.07	0.52	2	-5, 10	0.53

¹Number of observations (%).

²Average changes in α -diversity indices when the level of exposure to the biomarker is multiplied by Euler number e or compared to the reference category; adjusted for MiSeq analytic batch effect, child age at feces collection, delivery mode, gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one year), period of introduction of solid food, breast-feeding status up to 48 weeks, antibiotics use during the first year of life, presence of pets at home, passive smoking during the first year of life, and maternal characteristics (parity, age and body mass index (BMI) before pregnancy, education, and smoking status during pregnancy).

³CI: Confidence Interval.

1243 Table 2: Adjusted associations between concentrations of pollutants without a priori known antimicrobial properties and the α-diversity of the child gut

microbiota at one year (n between 334 and 349 mother-child pairs).

Chamical and amaguna window			Specific richne			Shannon diversi		Faith's phylogenetic diversity		
Chemical and exposure window	\mathbf{N}^{I}	Beta ²	95% CI ³	p-value ⁴	Beta ²	95% CI ³	p-value ⁴	Beta ²	95% CI³	p-value
Bisphenol A				-			_			-
Mother, pregnancy trim. 2	349	-0.6	-4, 3	0.55	0.02	-0.05, 0.09	0.59	-1	-11, 8	0.77
Mother, pregnancy trim. 3	344	1	-2, 4	0.34	0.06	0.00, 0.12	0.07	4	-4, 13	0.33
Child, 2 months	338	0.6	-1, 3	0.45	0.03	-0.01, 0.07	0.15	2	-4, 8	0.51
Child, 12 months	345	1	-2, 4	0.42	0.04	-0.02, 0.10	0.24	3	-5, 12	0.43
Bisphenol S										
Mother, pregnancy trim. 2				0.39			0.48			0.57
<lod< td=""><td>255 (73%)</td><td></td><td></td><td></td><td></td><td>_</td><td></td><td>_</td><td></td><td></td></lod<>	255 (73%)					_		_		
>LOD	94 (27%)	-2	-9, 4		-0.05	-0.19, 0.09		-6	-25, 14	
Mother, pregnancy trim. 3				0.57		· · · · · · · · · · · · · · · · · · ·	0.97		· · · · · · · · · · · · · · · · · · ·	0.91
<lod< td=""><td>252 (73%)</td><td>_</td><td></td><td></td><td>_</td><td>_</td><td></td><td>_</td><td>_</td><td></td></lod<>	252 (73%)	_			_	_		_	_	
>LOD	92 (27%)	-0.9	-7,6		0	-0.13, 0.14		1	-17, 20	
Child, 2 months	~ /		,	0.06			0.08			0.08
<lod< td=""><td>182 (54%)</td><td>_</td><td></td><td></td><td>_</td><td>_</td><td></td><td>_</td><td>_</td><td></td></lod<>	182 (54%)	_			_	_		_	_	
>LOD	156 (46%)	6	-0.5, 12		0.11	-0.01, 0.24		16	-2, 33	
Child, 12 months			,	0.57		,	0.21		7	0.63
<lod< td=""><td>102 (30%)</td><td>_</td><td></td><td></td><td>_</td><td>_</td><td></td><td>_</td><td>_</td><td></td></lod<>	102 (30%)	_			_	_		_	_	
LOD-LOQ	82 (24%)	-3	-11, 5	0.49	-0.16	-0.33, 0.02	0.08	-11	-34, 13	0.38
>LOQ	161 (47%)	-3	-11, 4	0.36	-0.06	-0.21, 0.09	0.42	-9	-29, 12	0.41
Benzophenone 3			,			,			- 1	
Mother, pregnancy trim. 2	349	-2	-4, 0.4	0.10	-0.01	-0.05, 0.03	0.67	-5	-11, 0.4	0.07
Mother, pregnancy trim. 3	344	-0.6	-3, 1	0.46	0.03	-0.01, 0.07	0.20	-2	-8,4	0.55
Child, 2 months	338	0.9	-1, 3	0.37	0.04	-0.01, 0.08	0.12	2	-4, 9	0.46
Child, 12 months	345	2	-1, 6	0.15	0.05	-0.02, 0.12	0.16	6	-3, 15	0.18
PFOA , Mother, pregnancy trim. 2	334	0.7	-6, 7	0.59	0	-0.14, 0.14	>0.99	2	-17, 21	0.82
PFNA , Mother, pregnancy trim. 2	334	-2	-10, 6	0.48	0.01	-0.16, 0.17	0.95	-7	-29, 15	0.52
PFHxS , Mother, pregnancy trim. 2	334	3	-3, 8	0.30	0.07	-0.04, 0.18	0.22	6	-9,22	0.42
PFOS , Mother, pregnancy trim. 2	334	1	-5, 7	0.54	0.03	-0.09, 0.15	0.65	2	-14, 18	0.78
PFDA Mother, pregnancy trim. 2	334	0.8	-5, 7	0.58	0.01	-0.12, 0.14	0.88	2	-16, 20	0.84
PFUnDA , Mother, pregnancy trim. 2	334	-1	-8, 5	0.54	0	-0.14, 0.15	0.95	-5	-24, 14	0.62
PFHpS , Mother, pregnancy trim. 2	334	2	-4, 7	0.45	0.03	-0.08, 0.14	0.60	2	-13, 17	0.77
PFDoDa , Mother, pregnancy trim. 2			,	0.51			0.87			0.70
<lod< td=""><td>34 (10%)</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></lod<>	34 (10%)									
LOD-LOQ	245 (73%)	5	-5, 15	0.32	0.04	-0.17, 0.25	0.69	12	-16,40	0.40
>L00	55 (16%)	3	-9, 15	0.60	0.07	-0.19, 0.32	0.60	10	-25, 44	0.58
PFHxPA , Mother, pregnancy trim. 2		-	- 7 -	0.88			0.76	-	- /	0.98
<lod< td=""><td>51 (15%)</td><td></td><td></td><td></td><td>_</td><td></td><td></td><td>_</td><td>_</td><td></td></lod<>	51 (15%)				_			_	_	
LOD-LOQ	105 (31%)	0.5	-9, 10	0.91	-0.05	-0.24, 0.14	0.61	0.8	-25,27	0.95
>L00	178 (53%)	0.7	-8,9	0.87	0.05	-0.18, 0.18	>0.99	2	-22, 26	0.87
PFHpA , Mother, pregnancy trim. 2	110 (00,0)		0,7	0.62	~	0.10, 0.10	0.45	_	,	0.98

<lod< td=""><td>262 (78%)</td><td>—</td><td></td><td></td><td>_</td><td>—</td><td></td><td>—</td><td>—</td><td></td></lod<>	262 (78%)	—			_	—		—	—	
>LOD	72 (22%)	0	-7, 7		0.06	-0.09, 0.21		0.2	-20, 21	
PFTrDa, Mother, pregnancy trim. 2				0.31			0.40			0.51
<lod< td=""><td>110 (33%)</td><td>_</td><td></td><td></td><td>_</td><td>—</td><td></td><td>—</td><td></td><td></td></lod<>	110 (33%)	_			_	—		—		
LOD-LOQ	155 (46%)	4	-2, 11	0.21	0.03	-0.12, 0.17	0.70	11	-9, 30	0.28
>LOQ	69 (21%)	-0.1	-8, 8	0.99	-0.09	-0.26, 0.09	0.35	2	-22, 26	0.86
PFBS, Mother, pregnancy trim. 2				0.13			0.88			0.14
<lod< td=""><td>206 (62%)</td><td></td><td></td><td></td><td>_</td><td>—</td><td></td><td>—</td><td>—</td><td></td></lod<>	206 (62%)				_	—		—	—	
>LOD	128 (38%)	4	-2, 11		-0.01	-0.14, 0.12		13	-4, 30	
PFOSA, Mother, pregnancy trim. 2				0.60			0.30			0.75
<lod< td=""><td>227 (68%)</td><td>_</td><td></td><td></td><td>_</td><td>—</td><td></td><td>—</td><td></td><td></td></lod<>	227 (68%)	_			_	—		—		
>LOD	107 (32%)	-0.5	-7, 6		-0.07	-0.21, 0.06		-3	-21, 15	
6:2 diPAP, Mother, pregnancy trim. 2				0.31			0.96			0.48
<lod< td=""><td>263 (79%)</td><td>_</td><td></td><td></td><td>_</td><td>—</td><td></td><td>—</td><td></td><td></td></lod<>	263 (79%)	_			_	—		—		
>LOD	71 (21%)	-3	-10, 4		0	-0.16, 0.15		-7	-28, 13	
8:2 diPAP, Mother, pregnancy trim. 2				0.53			0.60			0.60
<lod< td=""><td>293 (88%)</td><td>—</td><td></td><td></td><td>_</td><td>—</td><td></td><td>—</td><td>—</td><td></td></lod<>	293 (88%)	—			_	—		—	—	
>LOD	41 (12%)	-2	-11, 7		-0.05	-0.24, 0.14		-7	-33, 19	

¹Number of observations (%).

²Average changes in α-diversity indices when the level of exposure to the biomarker is multiplied by Euler number e or compared to the reference category; adjusted for MiSeq analytic batch effect, child age at feces collection, delivery mode, gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one year), period of introduction of solid food, breast-feeding status up to 48 weeks, antibiotics use during the first year of life, presence of pets at home, passive smoking during the first year of life, and maternal characteristics (parity, age and body mass index (BMI) before pregnancy, education, and smoking status during pregnancy). ³CI: Confidence Interval.

⁴After correction for multiple testing, the significance threshold is 0.001.

1246 Table 3: Adjusted associations between levels of pollutants with a priori known

1247 antimicrobial properties (parabens, triclosan) and Bray-Curtis gut microbiota β -diversity

¹²⁴⁸ *in one-year children (n between 334 and 349 mother-child pairs).*

		Bray-Curtis	s dissimilarity	
Chemical and exposure window ¹	\mathbf{N}^2	Sum of squares ³	F-statistic ⁴	p-value
Methylparaben				
Mother, pregnancy trim. 2	349	0.76	1.11	0.27
Mother, pregnancy trim. 3	344	0.55	0.80	0.87
Child, 2 months	338	0.79	1.15	0.23
Child, 12 months	345	0.97	1.42	0.03
Ethylparaben				
Mother, pregnancy trim. 2	349	0.69	1.01	0.45
Mother, pregnancy trim. 3	344	0.89	1.31	0.08
Child, 2 months	338	0.28	0.81	0.72
Child, 12 months	345	0.88	1.28	0.08
Propylparaben				
Mother, pregnancy trim. 2	349	0.58	0.85	0.79
Mother, pregnancy trim. 3	344	0.62	0.90	0.68
Child, 2 months	338	0.34	0.98	0.45
Child, 12 months	345	1.13	1.66	0.008
Butylparaben				
Mother, pregnancy trim. 2	349	0.82	1.20	0.14
Mother, pregnancy trim. 3	344	0.81	1.18	0.17
Child, 2 months	338	0.38	1.13	0.29
Child, 12 months	345	0.68	1.00	0.46
Triclosan				
Mother, pregnancy trim. 2	349	0.61	0.89	0.69
Mother, pregnancy trim. 3	344	0.76	1.11	0.23
Child, 2 months	338	0.69	1.01	0.44
Child, 12 months	345	0.59	0.85	0.78

¹Most pollutants were coded as categorical variables (1st tertile, 2nd tertile and 3rd tertile) except ethylparaben at 2 months (<LOQ *vs* >LOQ), propylparaben and butylparaben at 2 months (<LOD *vs* >LOD) and butylparaben during 2nd and 3rd trimester of pregnancy and at 12 months (<LOD, LOD-LOQ, >LOQ).

²Number of observations.

³Variance in β -diversity that can be explained by differences in pollutant exposure between the different exposure groups; adjusted for MiSeq analytic batch effect, child age at feces collection, delivery mode, gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one year), period of introduction of solid food, breast-feeding status up to 48 weeks, antibiotics use during the first year of life, presence of pets at home, passive smoking during the first year of life, and maternal characteristics (parity, age and body mass index (BMI) before pregnancy, education, and smoking status during pregnancy).

⁴Ratio of the mean square between exposure level groups due to the pollutant exposure to the mean square within exposure level groups (error mean square).

1250 Table 4: Adjusted associations between levels of pollutants without a priori known

1251 antimicrobial properties and Bray-Curtis β -diversity in one-year children gut microbiota

^{1252 (}*n* between 334 and 349 mother-child pairs).

		Bray-Curtis	s dissimilarity	
		Sum of		
Chemical and exposure window ¹	N^2	squares ³	F-statistic ⁴	p-value ⁵
Bisphenol A				
Mother, pregnancy trim. 2	349	0.53	0.78	0.89
Mother, pregnancy trim. 3	344	0.88	1.29	0.08
Child, 2 months	338	0.72	1.06	0.36
Child, 12 months	345	0.67	0.98	0.50
Bisphenol S				
Mother, pregnancy trim. 2	349	0.27	0.79	0.78
Mother, pregnancy trim. 3	344	0.34	1.01	0.42
Child, 2 months	338	0.43	1.25	0.16
Child, 12 months	345	0.77	1.13	0.24
Benzophenone 3				
Mother, pregnancy trim. 2	349	0.89	1.30	0.07
Mother, pregnancy trim. 3	344	0.78	1.14	0.24
Child, 2 months	338	0.96	1.42	0.029
Child, 12 months	345	0.63	0.92	0.63
PFOA, Mother, pregnancy trim. 2	334	0.66	0.96	0.54
PFNA, Mother, pregnancy trim. 2	334	0.70	1.03	0.41
PFHxS, Mother, pregnancy trim. 2	334	0.79	1.16	0.17
PFOS, Mother, pregnancy trim. 2	334	0.90	1.31	0.06
PFDA, Mother, pregnancy trim. 2	334	0.59	0.87	0.74
PFUnDA , Mother, pregnancy trim. 2	334	0.84	1.23	0.12
PFHpS, Mother, pregnancy trim. 2	334	0.63	0.93	0.62
PFDoDa, Mother, pregnancy trim. 2	334	0.62	0.90	0.63
PFHxPA , Mother, pregnancy trim. 2	334	0.59	0.87	0.74
PFHpA, Mother, pregnancy trim. 2	334	0.32	0.95	0.54
PFTrDa, Mother, pregnancy trim. 2	334	0.87	1.28	0.08
PFBS, Mother, pregnancy trim. 2	334	0.20	0.59	0.97
PFOSA, Mother, pregnancy trim. 2	334	0.28	0.81	0.72
6:2diPAP, Mother, pregnancy trim. 2	334	0.37	1.09	0.33
8:2diPAP, Mother, pregnancy trim. 2	334	0.36	1.06	0.37

¹Most pollutants were coded as categorical variables (1st tertile, 2nd tertile and 3rd tertile) except bisphenol S during the 2nd and 3rd trimester and at 2 months, and PFHpA, PFBS, PFOSA, 6: 2 diPAP and 8:2 diPAP during 2nd trimester of pregnancy (<LOD *vs* >LOD) and bisphenol S at 12 months and PFDoDa, PFHxPA, PFTrDa during 2nd trimester of pregnancy (<LOD, LOD-LOQ, >LOQ). ²Number of observations.

³Variance in β -diversity that can be explained by differences in pollutant exposure between the different exposure groups; adjusted for MiSeq analytic batch effect, child age at feces collection, delivery mode, gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one year), period of introduction of solid food, breast-feeding status up to 48 weeks, antibiotics use during the first year of life, presence of pets at home, passive smoking during the first year of life, and maternal characteristics (parity, age and body mass index (BMI) before pregnancy, education, and smoking status during pregnancy).

⁴Ratio of the mean square between exposure level groups due to the pollutant exposure to the mean square within exposure level groups (error mean square).

⁵After correction for multiple testing, the significance threshold was 0.003.

1254 Table 5: Associations between concentrations of pollutants with identified effects on α -diversity or β -diversity and the 4 most abundant phyla in

1255 one-year children gut microbiota (n between 342 and 351 mother-child pairs).

Chemical and exposure		Ph	ıylum Firmicu	utes	Phy	lum Actinoba	cteria	Phy	lum Bacteroi	detes	Phy	lum Proteoba	cteria
window	N ¹	Beta ²	95% CI ³	p-value	Beta ²	95% CI ³	p-value	Beta ²	95% CI ³	p-value	Beta	95% CI ²	p-value
Methylparaben													
Child, 12 months	351	-0.1	-1, 0.9	0.91	-0.3	-1, 0.8	0.59	0.4	-0.5, 1	0.35	-1	-2, -0.2	0.01
Ethylparaben													
Mother, pregnancy trim. 3	350	2	0.1, 3	0.04	0.8	-0.9, 3	0.34	-0.9	-2, 0.5	0.2	-0.6	-2, 0.6	0.34
Propylparaben													
Child, 12 months	351	0.3	-0.4, 1	0.42	-0.4	-1, 0.4	0.31	0.5	-0.1, 1	0.13	-0.7	-1, -0.1	0.02
Butylparaben													
Child, 2 months				0.26			0.58			0.91			0.82
<lod< td=""><td>267 (78%)</td><td></td><td></td><td></td><td>_</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></lod<>	267 (78%)				_								
>LOD	75 (22%)	3	-2, 8		-2	-8,4		-0.3	-5, 5		0.5	-4, 5	

¹Number of observations (%).

 2 Average changes in relative abundances of major phyla when the level of exposure to the biomarker is multiplied by Euler number e or compared to the reference category; adjusted for MiSeq analytic batch effect, child age at feces collection, delivery mode, gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one year), period of introduction of solid food, breast-feeding status up to 48 weeks, antibiotics use during the first year of life, presence of pets at home, passive smoking during the first year of life, and maternal characteristics (parity, age and body mass index (BMI) before pregnancy, education, and smoking status during pregnancy).

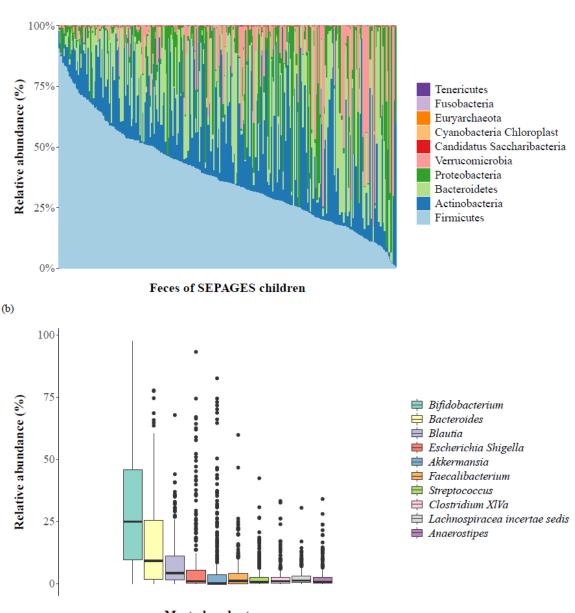
³CI: Confidence Interval.

1257 Figures

(a)

1258 Figure 1: Distribution of the most abundant taxa in gut microbiota in one-year children

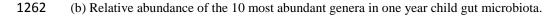




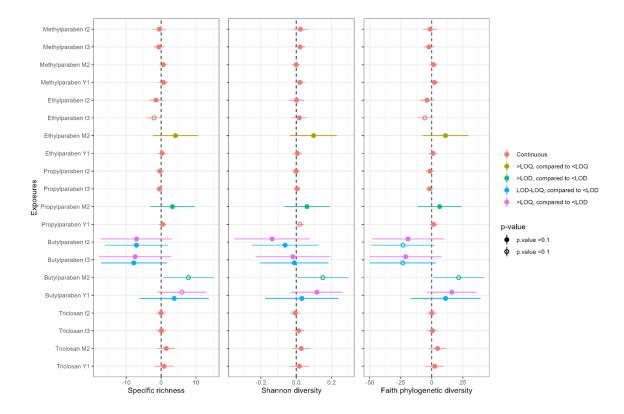
1260

Most abundant genera

1261 (a) Relative abundance of the phyla in one year child gut microbiota.



- 1263 Figure 2: Adjusted associations between concentrations of pollutants with a priori known
- 1264 antimicrobial properties and the α -diversity of the child gut microbiota at one year
- 1265 (adjusted single-pollutant models, n between 334 and 349 mother-child pairs).

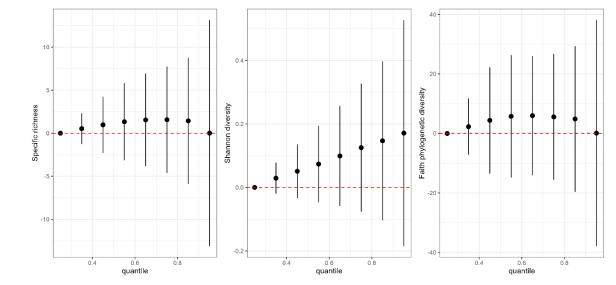


1266

1267 Average changes in α -diversity indices when the level of exposure to the biomarker is multiplied by Euler 1268 number e or compared to the reference category; adjusted for MiSeq analytic batch effect, child age at feces 1269 collection, delivery mode, gestational age, interpregnancy interval, child characteristics (sex, weight and 1270 length at birth and at one year), period of introduction of solid food, breast-feeding status up to 48 weeks, 1271 antibiotics use during the first year of life, presence of pets at home, passive smoking during the first year of 1272 life, and maternal characteristics (parity, age and body mass index (BMI) before pregnancy, education, and 1273 smoking status during pregnancy).

- 1274 t2: second trimester exposure, t3: third trimester exposure, M2: 2-month exposure, Y1: 12-month exposure.
- 1275 Details on the calculation of the α -diversity indices are given in the methods section.

- **1276** *Figure 3: Expected changes in* α *-diversity indices associated with concurrently increasing*
- 1277 quantiles of all chemicals (continuous variables), relative to when all concentrations were

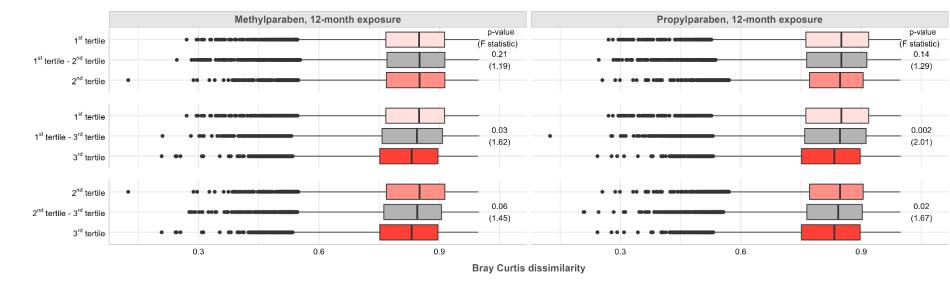


1278 fixed at their 25^{th} percentile (adjusted mixture models, n = 313 mother-child pairs).



1280 Mixture models are adjusted for MiSeq analytic batch effect, child age at feces collection, delivery mode, 1281 gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one year), 1282 period of introduction of solid food, breast-feeding status up to 48 weeks, antibiotics use during the first year 1283 of life, presence of pets at home, passive smoking during the first year of life, and maternal characteristics 1284 (parity, age and body mass index (BMI) before pregnancy, education, and smoking status during pregnancy). 1285 Details on the calculation of the α -diversity indices are given in the methods section.

1286 Figure 4: Adjusted associations between chemicals and children gut microbiota β-diversity at one year according to exposure levels in tertiles (n

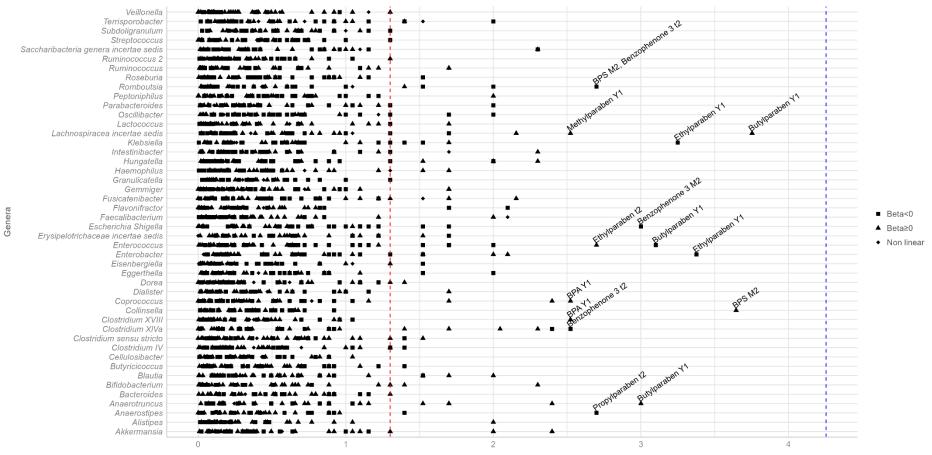


1287 = 345 mother-child pairs).

PERMANOVA models were adjusted for MiSeq analytic batch effect, child age at feces collection, delivery mode, gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one year), period of introduction of solid food, breast-feeding status up to 48 weeks, antibiotics use during the first year of life, presence of pets at home, passive smoking during the first year of life, and maternal characteristics (parity, age and body mass index (BMI) before pregnancy, education, and smoking status during pregnancy).

1294 Figure 5: Adjusted associations between concentrations of pollutants and the 46 most abundant genera in the child gut microbiota at one year

1295 (adjusted single-pollutant models, n between 340 and 355 mother-child pairs).

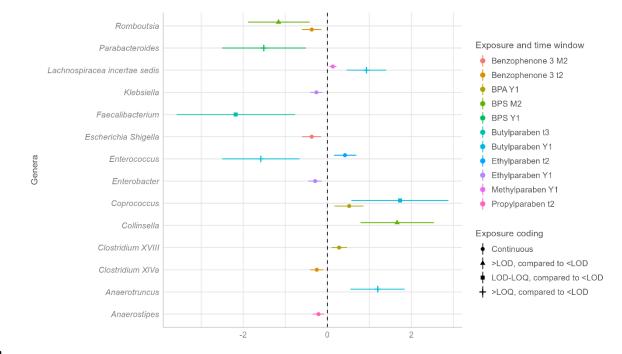


-log10(P-value)

-log10(p-value) of the associations between the pollutants and the 46 most abundant genera (detected in at least 30% of the children) when the level of exposure to the
 biomarker is multiplied by Euler number e or compared to the reference category, adjusted for MiSeq analytic batch effect, child age at feces collection, delivery mode,

- 1299 gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one year), period of introduction of solid food, breast-feeding status up to
- 1300 48 weeks, antibiotics use during the first year of life, presence of pets at home, passive smoking during the first year of life, and maternal characteristics (parity, age and body
- 1301 mass index (BMI) before pregnancy, education, and smoking status during pregnancy).
- 1302 The vertical red dotted line represents a p-value equal to 0.05. The vertical blue dotted line represented the threshold for the multiple testing corrected p-value (5.6x10⁻⁵).
- 1303 t2: second trimester exposure, t3: third trimester exposure, M2: 2-month exposure, Y1: 12-month exposure, BPA: bisphenol A, BPS: bisphenol S.
- 1304 S13. Complete results of the associations between pollutant exposures and the 46 most abundant are given Table genera

- 1305 Figure 6: Strongest adjusted associations between concentrations of pollutants and the 46
- 1306 most abundant genera in the child gut microbiota at one year (adjusted single-pollutant



1307 models, n between 340 and 355 mother-child pairs).

1308

1309 Average changes in the relative abundance of the most abundant genera (detected in at least 30% of the 1310 children) when the level of exposure to the biomarker is multiplied by Euler number e or compared to the 1311 reference category; adjusted for MiSeq analytic batch effect, child age at feces collection, delivery mode, 1312 gestational age, interpregnancy interval, child characteristics (sex, weight and length at birth and at one year), 1313 period of introduction of solid food, breast-feeding status up to 48 weeks, antibiotics use during the first year 1314 of life, presence of pets at home, passive smoking during the first year of life, and maternal characteristics 1315 (parity, age and body mass index (BMI) before pregnancy, education, and smoking status during pregnancy). 1316 t2: second trimester exposure, t3: third trimester exposure, M2: 2-month exposure, Y1: 12-month exposure, 1317 BPA: bisphenol A, BPS: bisphenol S.

1318 Complete results of the associations between pollutant exposures and the 46 most abundant genera are given1319 Figure 5 and Table S13.